AEM: PS4

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Part I. Direct Matching

```
1.
```

```
qui{
    capture program drop make_table
   program define make_table
        syntax varlist(numeric)
            matrix table1 = J(4, 8, .)
            matrix colnames table1 = `varlist'
            matrix rownames table1 = trt_mean comp_mean diff_mean diff_se
            local i = 1
            foreach var in `varlist' {
                qui ttest `var', by(treat)
                matrix table1[1, i'] = round(r(mu_2), 0.01)
                matrix table1[2, `i'] = round(r(mu_1), 0.01)
                matrix table1[3, i'] = round(r(mu_1)-r(mu_2), 0.01)
                matrix table1[4, `i'] = round(r(se), 0.01)
                local i = i'+1
            }
            matrix list table1
    end
}
use "nsw_dw.dta", clear
keep if data_id == "Dehejia-Wahba Sample"
make_table age education black hispanic nodegree married re74 re75
                                                                                               re75
                 age
                      education
                                      black
                                              hispanic
                                                         nodegree
                                                                     married
                                                                                    re74
trt_mean
               25.82
                          10.35
                                        .84
                                                   .06
                                                              .71
                                                                          .19
                                                                                 2095.57
                                                                                            1532.06
comp mean
               25.05
                          10.09
                                        .83
                                                   .11
                                                              .83
                                                                         .15
                                                                                 2107.03
                                                                                            1266.91
                                                   .05
diff_mean
                -.76
                           -.26
                                       -.02
                                                              .13
                                                                        -.04
                                                                                   11.45
                                                                                            -265.15
 diff_se
                 .68
                             .17
                                        .04
                                                   .03
                                                               .04
                                                                          .04
                                                                                  516.48
                                                                                             303.16
use "nsw_dw.dta", clear
drop if data_id == "Dehejia-Wahba Sample" & treat == 0
```

make_table age education black hispanic nodegree married re74 re75

	age	education	black	hispanic	nodegree	married	re74	re75
trt_mean	25.82	10.35	.84	.06	.71	.19	2095.57	1532.06
comp_mean	34.85	12.12	.25	.03	.31	.87	19428.75	19063.34
diff_mean	9.03	1.77	59	03	4	.68	17333.17	17531.28
diff_se	.78	.23	.03	.01	.04	.03	990.69	1001.91

The non-experimental comparison and treatment group are highly imbalanced across these covariates compared to the experimental treatment adn control group. There are very large (and statistically significant) differences between the treatment and non-experimental comparison group that suggest that the comparison group would have much higher earnings than the treatment group.

2.

```
use "nsw_dw.dta", clear
drop if data_id == "Dehejia-Wahba Sample" & treat == 0
* Prep data sets for mergin back in after matching procedure
* create id and index vars to match on
gen id = _n
gen index = _n
* rename variables to accomdate wide format created by matching
preserve
rename * *_1m
rename id_1m id
save "treat", replace
restore
preserve
rename * *_Om
rename index_Om index
save "comparison", replace
restore
```

nnmatch re78 treat re74 re75, keep(match_info) replace

re78	Coef.	Std. Err.	z	P> z	[95% Conf.	<pre>Interval]</pre>
SATE	-10475.37	3936.875	-2.66	0.008	-18191.5	-2759.233

The estimated treatment effect is -10475.37. This is in the opposite direction, and much larget than experimental treatment effect.

```
use "match_info", clear
keep if treat == 1
* merge back in other covariates dropped in matching process
merge m:1 id using "treat", ///
    keepusing(age 1m education 1m black 1m hispanic 1m married 1m nodegree 1m) ///
    keep(master match) nogen
merge m:1 index using "comparison", ///
    keepusing(age_Om education_Om black_Om hispanic_Om married_Om nodegree_Om) ///
    keep(master match) nogen
* get one row per observation (from tie matches)
collapse (mean) re74_* re75_* education_* index, by(id)
* check quality of matching for re74
reg re74_0m re74_1m
    * R-squared
                     = 0.9977
twoway (scatter re74_0m re74_1m) (lfit re74_0m re74_1m) \mid \mid ///
    function y = x, ra(re74_0m) clpat(dash)
The observations are being very well matched on re74. Regressing the matched re74 on the treatment re74
the R-Squared is 0.9977.
* check quality of matching for re74
reg re75_0m re75_1m
    * R-squared
                  = 0.9929
twoway (scatter re75_0m re75_1m) (lfit re75_0m re75_1m) \parallel \parallel ///
    function y = x, ra(re75_0m) clpat(dash)
The observations are also being very well matched on re75. Regressing the matched re75 on the treatment
re75 the R-Squared is 0.9929.
```

3.

```
* check balance of education treatment and matched comparison
ttest education_1m == education_0m
    * mean(diff) -.9477146 (se) .2238233
twoway (scatter education_0m education_1m) (lfit education_0m education_1m) || ///
   function y = x, ra(education_0m) clpat(dash)
```

Education is being very poorly matched when using only the pre-treatment income variables. The mean difference between the treatment and matched education is .95 years, and is statistically significant.

4.

```
use "nsw_dw.dta", clear
```

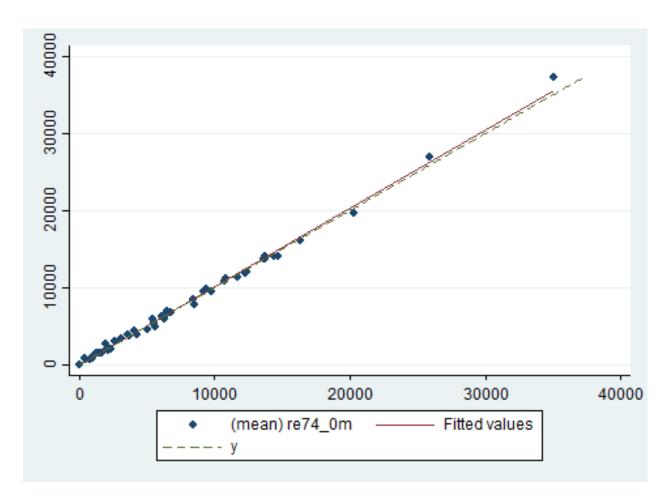


Figure 1:

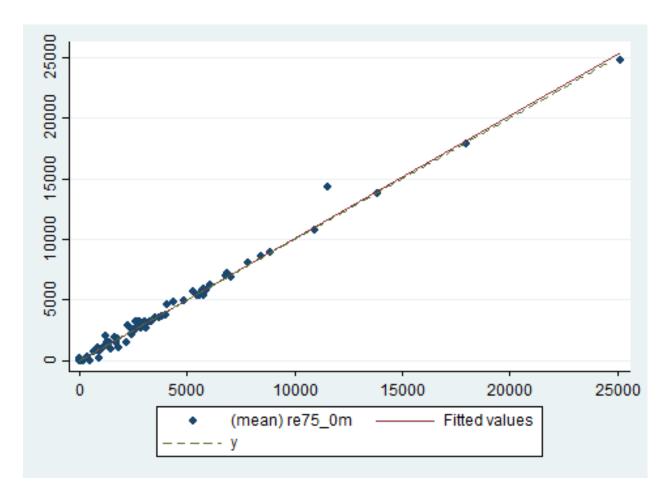


Figure 2:

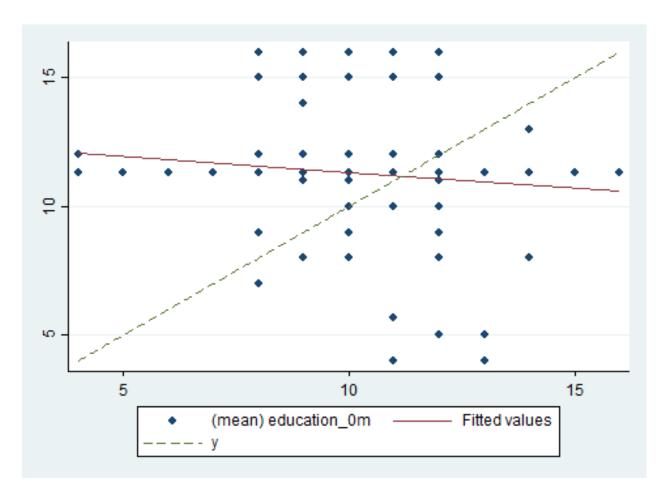


Figure 3:

```
drop if data_id == "Dehejia-Wahba Sample" & treat == 0
gen re74 sq = re74 ^{\circ} 2
gen re75_sq = re75^2
local covariates "education black hispanic married re74 re75 re74_sq re75_sq"
nnmatch re78 treat `covariates', keep(match_info2) replace
                Coef. Std. Err. z P>|z| [95% Conf. Interval]
       re78 |
*-----
      SATE | -11653.45 3990.061 -2.92 0.003 -19473.83 -3833.078
use "match_info2", clear
keep if treat == 1
* merge back in other covariates dropped in matching process
merge m:1 id using "treat", keepusing(age nodegree_1m) keep(master match) nogen
merge m:1 index using "comparison", keepusing(age nodegree_0m) keep(master match) nogen
drop re74 re75 re74_sq re75_sq
local collapse_vars = "treat re78_* age_* education_* black_* hispanic_* nodegree_* married_* re74_* re
collapse (mean) `collapse_vars', by(id)
local vars "age education black hispanic nodegree married re74 re75"
matrix table1 = J(3, 8, .)
matrix colnames table1 = `vars'
matrix rownames table1 = trt_mean comp_mean diff_se
matrix list table1
local i = 1
foreach var in `vars' {
   qui ttest `var'_0m == `var'_1m
   matrix table1[1, i'] = round(r(mu_2), 0.01)
   matrix table1[2, `i'] = round(r(mu_1), 0.01)
   matrix table1[3, i'] = round(r(se), 0.01)
   local i = i'+1
}
* Assess the quality of the matches for each covariate
matrix list table1
            age education black hispanic nodegree married re74
* trt_mean 25.82 10.35 .84 .06 .71 .19 2095.57 1532.06
*comp_mean 29.34 10.3 .84
                                             .71
                                                     .19 2521.42 1712.76
                                     .06
```

The matched comparison group is now much better matched with the treatment group acrossthese covariates, however the comparison group is still more than 3 years older on average, and makes more than \$400 more than the treatment group in 1974.

ttest re78_1 == re78_0

use "nsw_dw.dta", clear
keep if data_id == "Dehejia-Wahba Sample"
ttest re78, by(treat)

* Experimental treatment effect estimate

* -----

Group	-	Obs	Mean	Std. Err.	Std. Dev.		Interval]
Control Treated		260 185	4554.801 6349.144	340.0931 578.4229	5483.836 7867.402	3885.102 5207.949	5224.501 7490.338
diff			-1794.342	632.8534		-3038.11	-550.5745

The estimated treatment effect using the matching method is 1397.78 while experimental treatment effect estimate is 1794.34.

Part II. Propensity Score Matching

5.

```
use "nsw_dw.dta", clear
drop if data_id == "Dehejia-Wahba Sample" & treat == 0
gen re74_sq = re74 ^ 2
gen re75_sq = re75 ^ 2
local spec_5_vars "education black hispanic married re74 re75 re74_sq re75_sq"
qui logit treat `spec_5_vars'
predict p_score
save "spec_5", replace
```

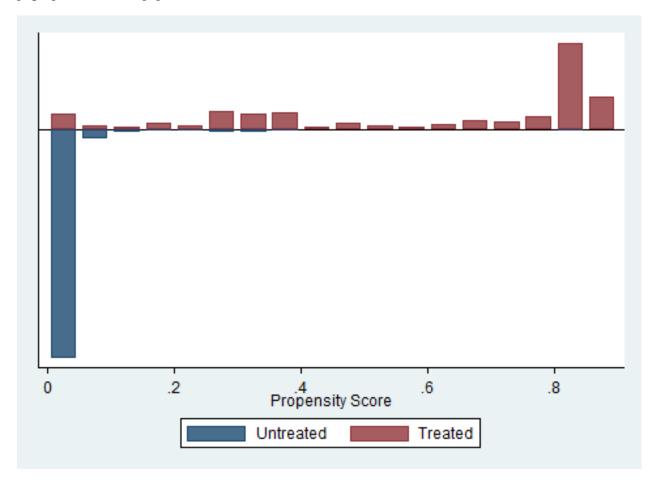


Figure 4:

* randomize sort of dataset so ties are matched at random set seed 20161206 gen u = uniform() sort u

psmatch2 treat, pscore(p_score) outcome(re78) neighbor(1) ate
local covariates "age education black hispanic nodegree married re74 re75"
pstest `covariates'

/*

Variable	 M Treated	ean Control	 %bias	 t-t t	est p> t	V(T)/ V(C)
age education	-+ 25.816 10.346	28.627 10.605	-31.4 -10.0	-3.09 -1.09	0.002 0.275	0.50* 0.63*
black	1 .84324	.84324	0.0	-0.00	1.000	
hispanic	1 .05946	.04865	5.2	0.46	0.647	
nodegree	.70811	.56757	30.7	2.84	0.005	•

married	.18919	.15676	8.8	0.82	0.411	
re74	2095.6	1920.3	1.7	0.40	0.693	1.91*
re75	1532.1	1832.1	-3.0	-0.81	0.421	0.68*

*/

The covariates are very well balanced for everything except age and nodegree, where the comparison group is older and more likely to have a degree. Both of these differences are statistically significant.

6.

* Propensity score matched treatment effect estimate ------

Variable	-			Difference	S.E.	T-stat
	Unmatched ATT	6349.1435 6349.1435	21553.9209 4584.23534	-15204.7774 1764.90816 -15446.032 -14255.7427		-13.17 0.93

* Experimental treatment effect estimate

Cmaun		 Obs	Mean	C+d Enn	Std. Dev.	[95% Conf.	11
Group	-			Std. Err. 			Incerval]
Control	l	260	4554.801	340.0931	5483.836	3885.102	5224.501
Treated	•	185	6349.144	578.4229	7867.402	5207.949	7490.338
diff			-1794.342	632.8534		-3038.11	-550.5745

Propensity score matched treatment effect estimate is 1764.91 while the experimental treatment effect estimate is 1794.34, so this matching method is working extremely well.

7.

Given that the matches in the above specification were not well ballanced for age and nodegree it's possible that the propensity score specification can be improved by adding these variables. Below I estimate the propensity score with all the variables from the previous specification and add age, age-squared, no degree, and an interaction term for education and nodegree.

```
use "nsw_dw.dta", clear
drop if data_id == "Dehejia-Wahba Sample" & treat == 0
gen re74_sq = re74 ^ 2
gen re75_sq = re75 ^ 2
gen age_sq = age ^ 2
gen educ_nodegree = education*nodegree
```

```
local spec_7_vars "age age_sq education black hispanic nodegree educ_nodegree married re74 re75 re74_sq qui logit treat `spec_7_vars' predict p_score
```

psgraph, t(treat) p(p_score)

save "spec_7", replace

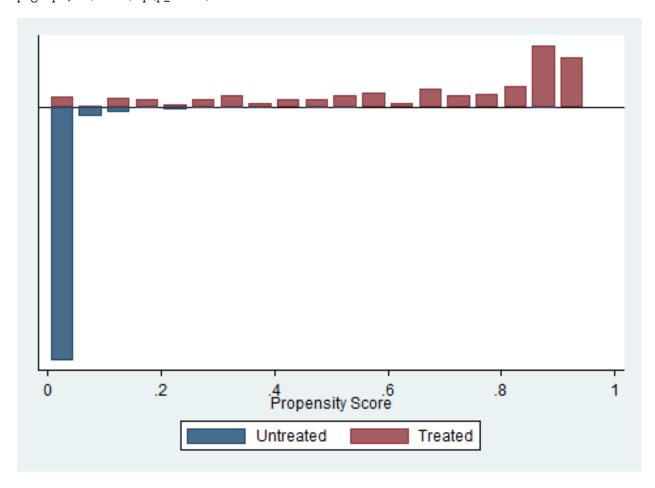


Figure 5:

```
* randomize sort of dataset so ties are matched at random
set seed 20161206
gen u = uniform()
sort u

psmatch2 treat, pscore(p_score) outcome(re78) neighbor(1) ate

local covariates "age education black hispanic nodegree married re74 re75"
pstest `covariates'
```

Variable	Treated		 %bias	t	est p> t	V(T)/ V(C)
age education black hispanic	25.816 10.346 .84324 .05946	25.827 10.184 .87027 .04865	-0.1 6.2 -6.7 5.2	-0.02 0.75 -0.74 0.46	0.988 0.453 0.459 0.647	1.24
nodegree married re74 re75	.70811 .18919 2095.6 1532.1	.6973 .12432 2397.7 2046	2.4 17.6 -3.0 -5.2	0.23 1.72 -0.68 -1.63	0.821 0.087 0.495 0.105	1.94* 1.28

This new specification achieves much better balance across all the covariates. Now there are no signiciant differences between the treatment and comparisons groups on any of these covariates.

* Propensity score matched treatment effect estimate

Variable	Sample	Controls	Difference	S.E.	T-stat
re78	Unmatched ATT ATU ATE	21553.9209 5494.63469	-15204.7774 854.50881 -14960.3169 -13866.5813	1154.61433 1299.69314	-13.17 0.66

* Experimental treatment effect estimate

Group	•	Mean	Std. Err.			. Interval]
Control Treated	260 185	4554.801 6349.144	340.0931 578.4229	5483.836 7867.402	3885.102 5207.949	5224.501 7490.338
diff		-1794.342	632.8534		-3038.11	-550.5745

However

Part III. Propensity Score Weighting

8.

```
use "nsw_dw.dta", clear
drop if data_id == "Dehejia-Wahba Sample" & treat == 0
gen re74_sq = re74 ^ 2
```

```
gen re75_sq = re75 ^2
gen age_sq = age ^ 2
gen educ_nodegree = education*nodegree
local spec_5_vars "education black hispanic married re74 re75 re74_sq re75_sq"
qui logit treat `spec_5_vars'
predict p_score
gen ipw = 1 / p_score if treat == 1
replace ipw = 1 / (1 - p_score) if treat == 0
reg re78 treat `spec_5_vars'
drop p_score ipw
      re78 | Coef. Std. Err. t P>|t| [95% Conf. Interval]
______
     treat | 1657.51 927.1529 1.79 0.074 -160.502
                                                        3475.522
______
local spec_7_vars "age age_sq education black hispanic nodegree educ_nodegree married re74 re75 re74_sq
qui logit treat `spec_7_vars'
predict p_score
gen ipw = 1 / p_score if treat == 1
replace ipw = 1 / (1 - p_score) if treat == 0
reg re78 treat `spec_7_vars'
```

re78		-	[95% Conf	. Interval]
			-396.9721	3278.253

The estimate the treatment effect via inverse propensity score weighting is 1657.51 using the first specification and 1440.64 using the second specification with additional covariates added to the estimation of the propensity score.